International Journal of Mechanical and Production Engineering Research and Development (IJMPERD)
ISSN (P): 2249-6890; ISSN (E): 2249-8001
Vol. 9, Issue 2, Apr 2019, 777-788

Original Article

EQUIVALENT STRESS PREDICTION OF AUTOMOBILE STRUCTURAL MEMBER USING FEA-ANN TECHNIQUE

P. V. SENTHIIL[1], V. S. AAKASH SIRUSSHTI[2] & T. SATHISH[3]

[1]*Professor and Head, Department of Automobile Engineering, SIMATS, SSE, Thandalam, Chennai, Tamil Nadu, India*

[2]*Graduate Research Assistant, M. S Industrial and Systems Engineering Program, Wayne State University, Michigan State, USA*

[3]*Associate Professor, Department of Mechanical Engineering, SMR East Coast College of Engineering and Technology, Somanathapattinam, Thanjavur, Tamil Nadu, India*

ABSTRACT

The backbone Chassis works for supporting the body and assorted pieces of the automobile. It should be adequately inflexible to persevere through the shock, twist, vibration and extra stresses. At that point, an imperative thought in case configuration is the quality (Equivalent Stress) for adequate twisting solidness. Essential objective of the examination is to develop an ANN model for indistinguishable stress forecast. Combined of two side individuals with a progression of cross individuals makes the body outline. Quantity of cross individuals, cross-segment, their areas, cross individuals and sizes of the side transform into the structure factors. From Creo 3. 0, it makes the chassis frame model and dismembered utilizing Ansys. As the quantity of parameters and levels are more, the likely models are excessively. At that point, performance of FEA apply on those models. Preparation of demonstrated ANN is to use the FEA's results. Having seen the calculation of standard back-engendering, it is the best choice for preparing the model for the ANN demonstrating. Use of multi-layer discernment organizes is for non-direct mapping between the info and yield parameters. FEA-ANN cross breed model can spare material utilized, creation time and cost.

KEYWORDS: Automobile Structural Member, Chassis Frame, FE Analysis, FEA-ANN Hybrid Modelling & Weight Reduction

Received: Feb 25, 2019; **Accepted**: Mar 15, 2019; **Published**: Mar 29, 2019; **Paper Id**.: IJMPERDAPR201977

1. INTRODUCTION

Frame of an automotive vehicles performs as a backbone or foundation. Combination of frame includes axles, vehicle wheels, suspensions and tires, which have made the principal load-carrying components of a vehicle [1]. Weight of the vehicle and its payload is carried by frame and other components [2]. Forces are transferred by both frame and suspension from axles to vehicle structure along with load carrying. Considering the drive forces and brake torque reaction, it moves the vehicle [3]. As a base, performance of frame is the body structure of vehicles, the engine/transmission package and the axles with their suspensions. The stiff frame is enough to support or carry all the loads and forces that the vehicle is subjected to in operation. A flexible frame is enough to handle shock loads and the ends, twists, bends, sag and sway. It encounters under different road or load conditions [4]. A flexible frame is also enough to fail even under normal operations. Ideally, the frame should work under different situations, while being able to return to its original shape when loads or forces are removed [5].

One of the most important challenges of automotive industry is to reduce fuel consumption and CO 2 as per European Commission of Research & Innovation in transport. By reducing a weight of the vehicle is one way to reduce consumption [6]. Thus, as result of reduced vehicle weight, objective of this project provides the basis to save millions of tonnes of fuel and carbon dioxide. Total fuel consumption of one-third of a passenger directly depend on its weight. The fuel saving of between 0. 3-0. 5 litres for every 100 km driven, according to industry estimates [Pratelli (1966)], represented by weight reduction of 100 kg [7].

In this work, objective is to prepare ANN model which can predict Equivalent Stress for Eicher 11. 10 chassis frame. As the chassis frame is analysed using the finite-element techniques [8]. Frame of Appropriate model is developed as the chassis frame is analysed using the finite-element techniques [9]. Changing the Parameters (Size Optimization) of the sidebar and crossbar achieve the weight reduction [10]. To obtain the best model, performance of FEA works on those models. Probable models are too many as the levels and numbers of parameters are more [11]. So, a large number of modelling and analysis work involves to select optimum parameters among them [12]. In research field, lately, structural optimization utilizing computational instruments becomes a noteworthy [13]. Normally, techniques are to be developed in the structural analysis and demand of the optimization is extensive computational expense which depend upon the issue unpredictability. To diminish the computational exertion without influencing the final solution quality, among these, ANN might be joined with established examination [14]. By using Artificial Neural Networks (ANN) methodology, Bourquina et al. (1998) analyse an experimental data from an arranging study which contrasted both graphically and numerically with established displaying systems. Finite-element method as a powerful tool has been established by Javadi et al. (2003) in the examination. Approximation of conduction of the actual material, in this numerical analysis, its idealized material deforms as per some constitutive connections [15].

By using an integrated environment, injection-moulded item was streamlined by spina et al. (2006) [16]. Execution of methodology is to examine the primary causes of defects and take focal points of the Finite Element (FE) Analysis to re-enact part manufacture. Declaration of assessment of the Finite Element recreation results through the Artificial Neural Network framework, it was a productive technique for the evaluation of the impact of procedure parameter minor departure from part manufacturability [17]. Another idea of finite-element method (FEM) and integrating artificial neural systems (ANN)was presented by Saltan et al. (2007) in displaying un bound material properties of the sub - base layer in adaptable asphalts. Huge number of various methodologies was embraced by Benardos et al. (2007) in order to manage this issue. It examined all parts of the artificial neural networks (ANN)'s displaying technique, from pre/post handling and training data collection, for expanding training plans and algorithms. Usage of a computational code and definition were shown by Cardozo et al. (2011)improves fabricated complex covered structures with a moderately low computational expense by combining ANN to estimate the finite-element solutions, Finite-Element Method (FEM) and Genetic Algorithms (GA) for basic enhancement.

2. EXPERIMENTAL METHODOLOGY

ST 52 is the material. Properties of the material which has been shown in Table 1.

Table 1: Material Properties of Chassis (Tech, 2003)

Material	ST 52
Modulus of Elasticity E	2 x 105 MPa
Poisson's Ratio	0. 3

Table 1: Contd.,	
Tensile Strength	520 MPa
Yield Strength	360 MPa

In statistical design of experiment, taguchi method is a collection of mathematical. The statistical techniquesis useful for the parametric optimization and analysis of problems influences the response of interest. The relationship between a set of quantitative experimental variablesand a response are examined by ANN. Figure 1 show flow chart of experiment.

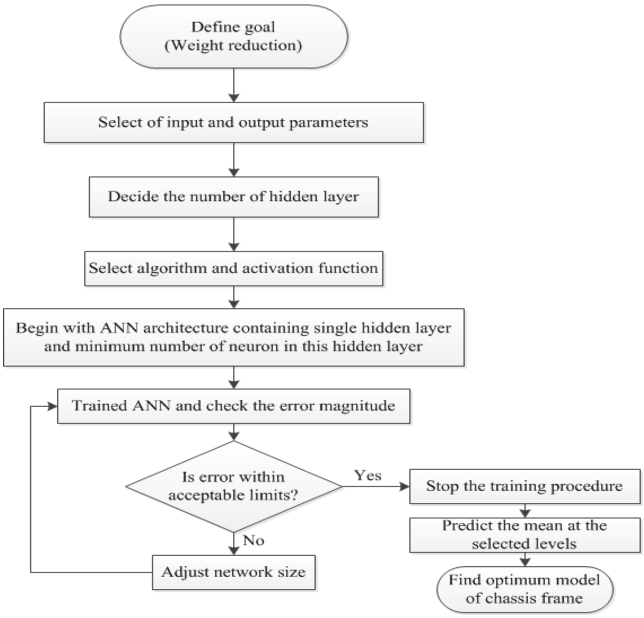


Figure 1: Flow Chart of Experiment

Experiments are planned based on Taguchi's L25 orthogonal array for web. Lower flange and Upper flange are shown in Figure 2. Having said 25 rows corresponding to the number of tests with 5 columns at five levels and 3 parameters, it has shown in Table 2. Orthogonal array is selectedbecause of its capability to check the interactions among factors.

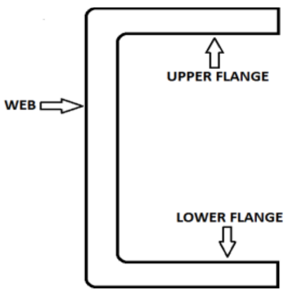


Figure 2: C Channel

Table 2: Factors and Their Levels

Factor	Level 1	Level 2	Level 3	Level 4	Level 5
Thickness of Web (mm)	3	4	5	6	7
Thickness of Upper flange (mm)	3	4	5	6	7
Thickness of Lower flange (mm)	3	4	5	6	7

Orthogonal arrays (OA) are the experimental designsby using specially constructed tables. In consistent way, design of experiments is very easy by using these tables.

By using ANSYS, we can measure lower flangeand upper flange, value of equivalent stress, weight and deflection. It can find out the optimum thickness of web. We can obtain the optimum weight for allowable stress and deflection condition through conduction of series of analysis. Established equivalent stress is more critical for analysis, so preparation of ANN model is to predict the equivalent stress by using data given in Table 3.

Table 3: Experimental Results Table

Number of Experiment No.	Factors			Equivalent Stress N/mm^2
	Thickness of Web (mm)	Thickness of Upper Flange (mm)	Thickness of Lower Flange (mm)	
Training Data Sets				
1	3	3	3	155. 01
2	3	4	4	128. 2
3	3	5	5	118. 16
4	3	6	6	115. 5
5	3	7	7	103. 39
6	4	3	4	118. 57
7	4	4	5	112. 42
8	4	5	6	102. 61
9	4	6	7	96. 97
10	4	7	3	131. 15
11	5	3	5	108. 04
12	5	4	6	97. 007
13	5	5	7	93. 031
14	5	6	3	121. 77
15	5	7	4	108. 2
16	6	3	6	97. 78
17	6	4	7	88. 38
18	6	5	3	110. 08
19	6	6	4	97. 607
20	6	7	5	88. 78
21	7	3	7	87. 279
22	7	4	3	100. 25
23	7	5	4	93. 288
24	7	6	5	86. 179
25	7	7	6	82. 599
Testing Data Sets				
26	3	3	5	140. 63
27	3	3	6	134. 97
28	3	4	5	123. 09
29	4	4	6	107. 53
30	4	6	4	113. 83
31	4	6	6	108. 39
32	5	4	4	111. 16
33	5	5	3	124. 86
34	5	5	5	106. 16
35	5	7	5	106. 45
36	6	4	4	98. 804
37	6	4	6	90. 704
38	6	6	6	88. 171
39	7	5	5	88. 478

3. ANN MODEL FOR EQUIVALENT STRESS PREDICTION/ ARTIFICIAL NEURAL NETWORK (ANN) APPROACH

Forecast ability over the regression models has been preferred by ANN models from literature reviews. The purpose of getting equivalent stress prediction, ANN models are also created . From this section, it explains pre-processes, model design and training, model simulation and post processes in the generation of ANN prediction models.

Converted data should be a range of 0 to 1 or -1 to 1 before applying inputs and outputsi. e. used normalized data for ANN training. Using the equation (1) calculates the data normalization, which ranges the data from o to 1.

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Where,

x_n = Normalized Value of Variable x

x = Value of Variable x

$x_{\min}$ = Minimum Value of variable x

$x_{\max}$ = Maximum Value of Variable x

Input data sets and targets data sets are made for preparing reason in the wake of normalizingdata. Target data sets include targets (standardized estimated proportional stress values) for separate input data sets. This proposed work incorporated a capacity estimation or expectation issue, which required the minimized final error to an extremely little value.

3. 1 Neural Network Design

Isolation of each of thirty-nineexperimental data setsused for preparing and testing. We can obtain the preparation ofdistinctive system setup with adifferentnumber of hiddenneuronsusing Neural Network Toolbox in MATLAB. For preparing and testing, it uses 25 orthogonal array data setsand 14 arbitrarily pick informational collections. To minimize the handling time in training, it improves the speculation ability of models anduses more data sets in ANN learning .

So usage of substantial number of data setsis to prepare the models. Levenberg-Marquardt (LM) improvement calculation has been used in this examination in order to discover weights and biases. This prepared calculation modifies them to decrease errors among target and anticipated output values. According to Demuth et al. 2009, LM can rapidly give precise outcomes if the quantity of neurons in hidden layers .

Utilizing LM calculation, MSE converges to a value near 0 and R2 combines to an esteem near one as soon as the quantity of neurons in the hidden layer achieves 6. On the other hand, this calculation tends in reality to over fit anticipated data in preparing, which keeps it from precisely summing up. For this situation, the network will in general remember training models excessively well and as a result, it can't give proficient forecasts for new conditions. So we can takenecessary test of ANN model on another data set collection within the preparation procedure and dothe check of picked structure gives great outcomes on arbitrary conditions.

At last, prepared ANN demonstrate with 3 layers: one hidden layer, one input layer and one output layer. Fixed quantities of neurons in the input and output layer, layer 3 and 1 separately. Development of one hidden layer with 10 neurons obtained in this proposed work. In the middle of input layer and output layer have used tansigtransfer function in this model, though in the middleof hiddenlayer and output layer used purelin function work.

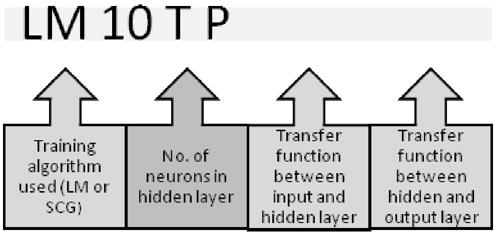


Figure 3: ANN Model Designation

Figure 3 recommends how this model got assigned. This assignment work covers different properties of the ANN model made. It includes different sorts ofprepared calculation utilized, number of neurons in the hidden layer, transfer function utilized in the middle of input and output layer.

Having standardized the information, input data records and targets data documents arranged for training. These information documents incorporate record for preparing and testing, which contains input informational collections in irregular request. Target information documents incorporate targets (standardized estimated comparable stress values) for preparing and testing. The work in this investigation contained an expectation issue, which required the minimized final errorto an extremely little value.

A feed-forward neural system with back propagationused in this model. The network comprises of three layers: one hidden layer, one output layer and one input layer. Fixed quantities of neurons in the input and output layer were 4 and 1 individually.

By using sigmoid activation work, it activates the input layer, while activating the second layer(hidden layer), and use ofdirect initiation work activates third layer (output layer)as appeared in Figure 4. A network of two exchange work, the marked principal transfer functionand direct second transfer function, prepared to inexact any capacity.

The prepared networkcan get byusing an appropriate managed learning calculation, for this situation, the Levenberg-Marquardt calculation. On account of supervised learning, the networkgives both input dataand outputdata called as preparation set. The balanced networkdepends upon on comparison of the output and target values until the output coordinate the objectives.

Networks are developed every one of them is prepared independently, and the best system is chosen dependent on the precision of the forecasts in the testing stage. Table 6. 3 demonstrates an act investigation depends upon on the quantity of neurons inhidden layer, MSE error value andR2 error value.

In this study, model used one hidden layer with 10 neurons and used tansig transfer functionin middle of input layer and output layer, where purelin transfer functionuesd inmiddle of hidden layer and output layer.

In this paper, the projectincluded forecast issue which required the minimizedfinalerror to a little esteem.

Figure 4 demonstrates general perspective on LM10TP display, where Figure 5 indicates improved perspective on LM10TP Model. Figure 6 demonstrates truncated perspective on LM10TP Model in MATLAB. Figure 7 indicates neural system tool stash demonstrate creation and preparing window of LM10TP display. Thebackpropagation modeltype utilized LM preparing calculation contains 20 neurons in hidden layer. Tansig, MSE execution work and purelin exchange work, which can use in the middle of input and hidden layer.

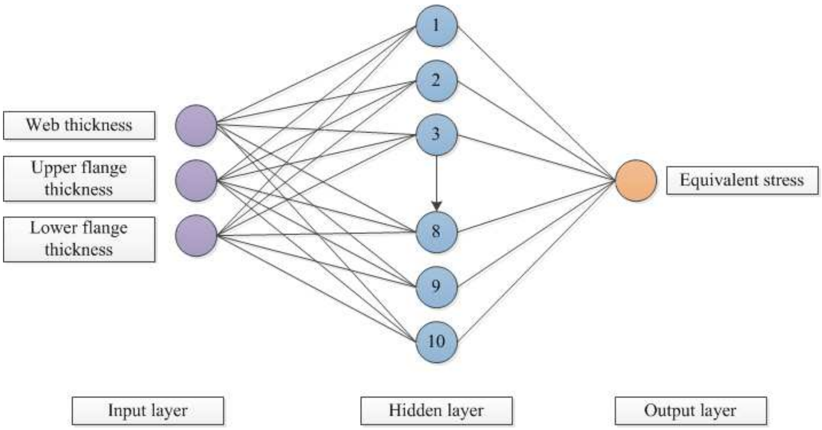


Figure 4: General View of LM10TP Model View with three Layers

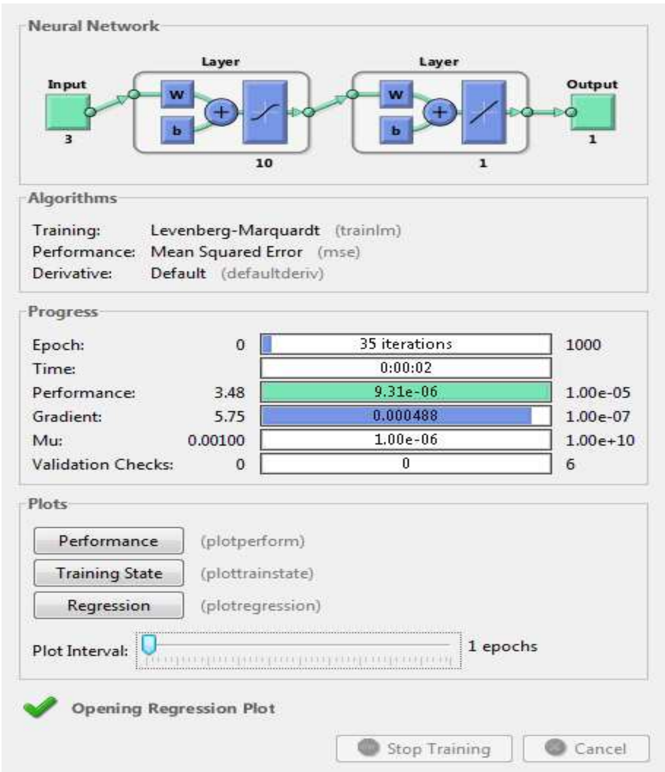


Figure 5: LM10TP Model Training

Figure 5 indicates neural system toolboxmodel creation and preparing window of LM10TP model. Usage of LM preparing algorithm is applied inback propagation model type. It has 10 neurons in concealed layer, MSE as an act work, tansig and purelin exchange capacities were utilized in the middle of info and shrouded layer and in the middle of a covered up and yield layers separately. i

Figure 5 appears, training execution (MSE) diagram of LM10TP demonstrate, made during its preparation. The preparation ceased after 35 epochs in light of the fact that the execution objective was accomplished. It is a valuable analytic tool to plot the errors to check the advancement of training.

The outcome here is sensible, because the testing set error and the test set error have comparative qualities, and it doesn't give the idea that any criticalness over fitting has happened. After beginning preparing of LM10TP demonstrate, it was retrained for 35 epochs and execution MSE acquired was 9. 3083×10-06 in preparing.

4. RESULTS AND DISCUSSIONS

4. 1. Post Processing

The procedure chose to check the expectation and speculation capacity of models is talked about in following sub segments.

Accuracy Checking of ANN Model

In order to understand, whether an ANN is making great expectations, test information, obtaining checked outcomes at this stage. For making correlations, we can use mean square error (MSE), root mean square error (RMSE) and the coefficients of various assurance (R2) values of measurable strategies. The accompanying conditions dictates these qualities.

$$RSME = \left[\frac{1}{n} \sum_{j=1}^{n} \left| a_j - p_j \right|^2 \right]^{\frac{1}{2}} \tag{2}$$

$$R^2 = 1 - \left[\frac{\sum_{j=1}^{n} (a_j - p_j)^2}{\sum_{j=1}^{n} (p_j)^2} \right] \tag{3}$$

By using MATLAB program, we can check the errors produced in the expectation model. Trained simulation ANN results sent into MATLAB workspace. After preparation, all checked outcomes obtained for three sorts of error terms. Finally, we can obtain the simulation results.

The estimations of root mean square error, mean square error and coefficient of assurance R2 for LM10TP engineering are9. 31×10-06, 0. 0031 and 0. 9999 individually in preparing. The estimations of root mean square error, mean square error, and coefficient of assurance R2 for LM10TP design are 2. 94×10-06, 0. 0017, and 0. 9999 individually in the testing. his demonstrated model was performing admirably in preparing and testing.

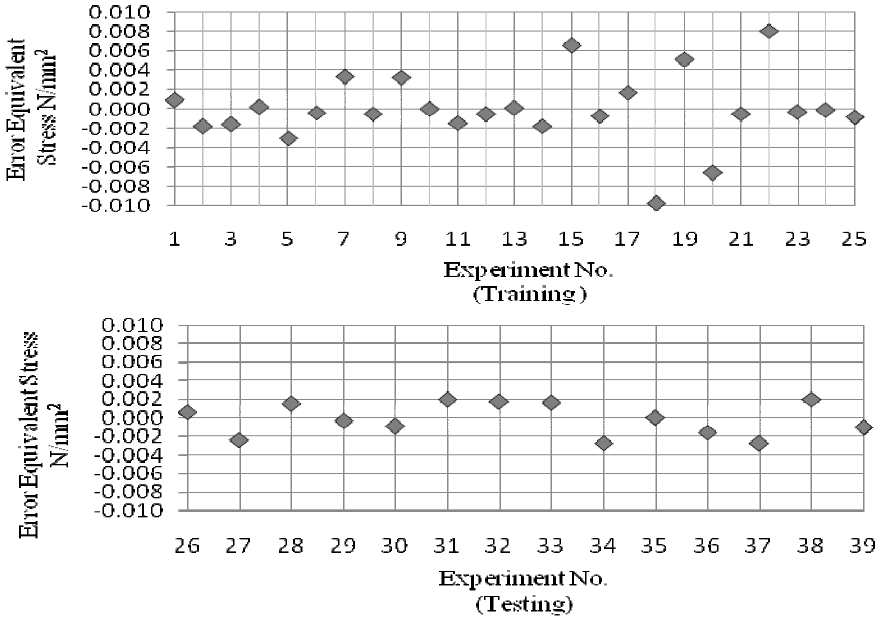


Figure 6: LM10TP Model Prediction Error

Prediction errors in training and testing for LM10TP model are shown in Figure 6.

4. 2 Weights and Bias for LM10TP

ANN model is trained by changing and storing proper weights in interconnection links between neurons lying in various layers. It weighs and Bias in connection links between input-hidden neurons as well as hidden-output neurons for LM10T Pare shown in Table 4.

Table 4: Weights in Connections of LM10TP Model

Weight Values				Bias Values	
Input – Hidden Layer			Hidden - Output Layer	Input -Hidden Layer	Hidden - Output Layer
3. 088791	-3. 13677	3. 889805	0. 051843	-5. 40792	0. 661618
6. 638475	4. 56653	-3. 4726	-0. 18134	-7. 19698	
-4. 16807	5. 922006	-0. 13991	-0. 03181	-1. 80375	
1. 411722	-1. 35175	1. 919875	-0. 21494	0. 408484	
0. 650439	4. 684998	6. 597881	-0. 06388	-4. 68118	
-4. 48549	-6. 65087	6. 877101	0. 61816	2. 309194	
-2. 19422	-3. 44074	3. 856856	-0. 73833	0. 96741	
3. 628453	6. 825887	-1. 07669	0. 141345	-3. 91142	
6. 444579	6. 576662	-1. 40225	1. 490443	-2. 37204	
4. 801634	4. 789042	-1. 256	-1. 89575	-1. 60621	

4. 3 The Equation for Output Prediction

For creating the ANN output with the assistance of weight, bias matrix and transfer function following equation is utilized.

For output of first layer

$$a1 = f1[(net.iw\{1,1\} \times p) + (net.b1\{1\})] \tag{4}$$

For output of second layer

$$a2 = f2[(net.lw\{2,1\} \times a1) + (net.b2\{2\})] \tag{5}$$

Where p is the input vector, b1 and b2 are the bias vector of hidden layer and output layer respectively, $f1$ represents the tansig transfer function and $f2$ represents purelin transfer function, iw and lw are the weight matrix of hidden layer and output layer respectively.

4. 4 Linear Regression Fitting of LM10TP Model

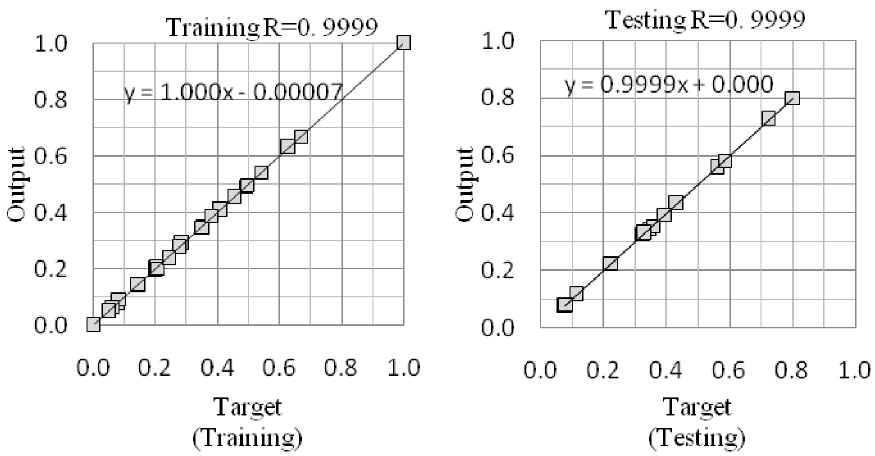
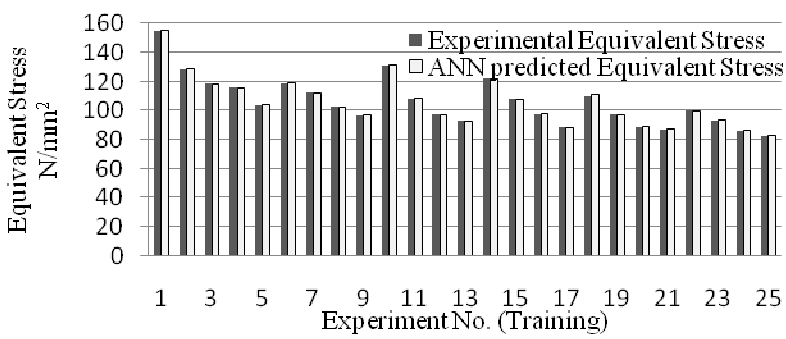


Figure 7: LM10TP Model Linear Fitting in Training and Testing

The network output andrelating targets are going to postreg. It returned three parameters. The m and b relate to the slant and the y - intercept. If this number is equivalent to 1, at that point, there is an ideal relationship amongst objectives and output. It performed between the network and the provided focuses for preparing and testing. Figure 7 (A) and (B) demonstrates, with three parameters m, b and R, the linear regression for preparing and testing of LM10TP model individually. Separate parameters and diagrams demonstrate of LM10TP modellinearly intently fits with the provided target values. Demonstration of model LM10TP is appropriate for proportionate stress expectation with high precision.

4. 5 Comparison of Experimental Results and Predicted LM10TP ANN Results



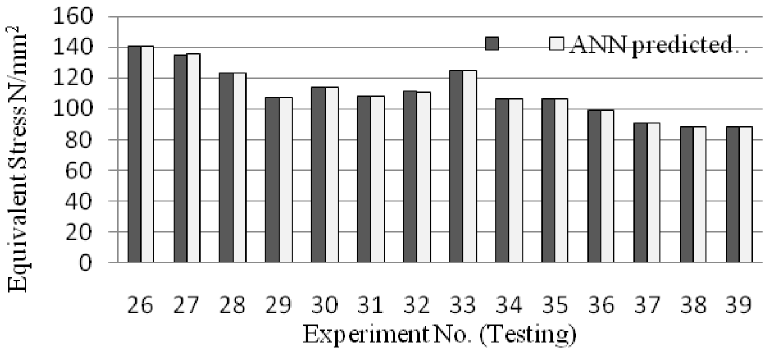


Figure 8: Actual vs. ANN Predicted Result in Training and Testing

Equivalent stress predicted by selecting LM10TP model was compared with the actual target in training, and testing is shown in Figure 8. Different colours and markers show the comparison. From the graph, absolutely, ANN predicted outcomes are extremely near actual targets.

5. CONCLUSIONS

Purpose of the study is to make the weight decrease of Eicher 11. 10 chassis frame. This weight decrease is done by creating proportionate pressure models dependent on L25 orthogonal array. Comparable stress expectation of ANN model reaches the accompanying determinations. The estimations of coefficient of assurance and mean square error for LM10TP architecture are 0. 9999 and 0. 0031 separately in preparing. Estimations of coefficient of assurance and mean square error for LM10TP engineering are 0. 9999 and0. 0017 individually in the testing. Each anticipated comparable stress estimation of the ANN is near experimental results. In additionally, absolutely, the ANN may be utilized as a good option for the investigation of the impacts of chassis outline parameters on the proportionate stress.

REFERENCES

1. *Benardos, P. G., & Vosniakos, G. C.,"Optimizing feedforward artificial neural network architecture. Engineering Applications of Artificial Intelligence, vol. 20, no. 3, pp. 365-382, 2007.*
2. *Bourquin, J., Schmidli, H.,van Hoogevest, P., & Leuenberger, H., "Comparison of artificial neural networks (ANN) with classical modelling techniques using different experimental designs and data from a galenical study on a solid dosage form. " European journal of pharmaceutical sciences, vol. 6, no. 4, no. 287-300, 1998.*
3. *Cardozo, S. D., Gomes, H., &Awruch, A., "Optimization of laminated composite plates and shells using genetic algorithms, neural networks and finite elements". Latin American Journal of Solids and Structures, vol. 8, no. 4, pp. 413-427, 2011.*
4. *Javadi, A. A.,Tan, T. P.,& Zhang, M.,"Neural network for constitutive modelling in finite element analysis. " Computer Assisted Mechanics and Engineering Sciences, vol. 10, no. 4, pp. 523-530, 2003.*
5. *Madan, D., Sivakandhan, C., Sagadevan, S., Sathish, T., "Ocean wave energy scenario in India", International Journal of Mechanical and Production Engineering Research and Development, vol. 8, no. Special Issue 6, pp. 582-590, 2018*
6. *George, J. P., & Pramod, V. R. (2014). An interpretive structural model (ISM) analysis approach in steel re rolling mills (SRRMS). International Journal of Research in Engineering & Technology (IMPACT: IJRET), 2(4), 161-174.*
7. *Pratelli, Antonio. &Brebbia, C. A.,"Urban Transport Seventeen", Part XVII (Southampton, UK: WIT Press), 1966.*
8. *Saltan, M., & Sezgin, H., "Hybrid neural network and finite element modeling of sub-base layer material properties in flexible pavements. " Materials & design, vol. 28, no. 5, pp. 1725-1730, 2007.*

9. Sathish, T.,"Heat transfer analysis of nano-fluid flow in a converging nozzle with different aspect ratios", Journal of New Materials for Electrochemical Systems, vol. 2, no. 4, pp. 161-167, 2017

10. Sathish, T.,"Performance measurement on extracted bio-diesel from waste plastic", Journal of Applied Fluid Mechanics, vol. 10, no. 1, pp. 41-50, 2017.

11. Sathish, T.,"Prediction of springback effect by the hybridisation of ANN with PSO in wipe bending process of sheet metal", Progress in Industrial Ecology, vol. 12, no. 1-2, pp. 112-119, 2018

12. Sathish, T.,Jayaprakash, J.,"Optimizing supply chain in reverse logistics", International Journal of Mechanical and Production Engineering Research and Development, vol. 7, no. 6, pp. 551-560, 2017.

13. Panneerselvam, K., & Lenin, K. (2013). Study on hardness and micro structural characterization of the friction stir welded Nylon 6 plate. Int J Mech Eng, 2, 51-62.

14. Sathish, T., Karthick, S.,"HAIWF-based fault detection and classification for industrial machine condition monitoring", Progress in Industrial Ecology, vol. 12, no. 1-2, pp. 46-58, 2018

15. Sathish, T., Periyasamy, P., Chandramohan, D., Nagabhooshanam, N., "Modelling K-nearest neighbour technique for the parameter prediction of cryogenic treated tool in surface roughness minimization", International Journal of Mechanical and Production Engineering Research and Development, Special Issue, pp. 705-710, 2018

16. Sathish, T., Periyasamy, P., Chandramohan, D., Nagabhooshanam, N., "Modelling of cost based optimization system E-O-L disassembly in reverse logistics", International Journal of Mechanical and Production Engineering Research and Development, Special Issue, pp. 711-716, 2018

17. Sathish, T.,Vijayakumar, M. D.,Krishnan Ayyangar, A.,"Design and Fabrication of Industrial Components Using 3D Printing", Materials Today: Proceedings, vol. 5, no. 6, pp. 14489-14498, 2018

18. Gopalakrishna, H. D., Panda, P., Jois, P., & PN, N. (2014). Crashworthiness of Automobile in a Vehicle-to-Pole Crash Simulation. International journal of automobile engineering research & development, ISSN (E), 2278-9413.

19. Spina, R.,"Optimization of injection moulded parts by using ANN-PSO approach. " Journal of Achievements in Materials and Manufacturing Engineering, vol. 15, no. 1-2, pp. 146-152, 2006.

20. Tech, P. S. G.,"Design Data Book". KalaikathirAchchagam, Coimbatore, 2003.